





Science of Information, Computation and Fusion

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Tristan Nguyen
Program Manager
AFOSR/RSL
Air Force Research Laboratory



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2012 AFOSR SPRING REVIEW



NAME: Science of Information, Computation and Fusion

BRIEF DESCRIPTION OF PORTFOLIO:

Information fusion requires understanding of information across multiple domains. Challenges: (1) how to formalize domains of knowledge and information – structures and their interconnection; (2) how to mechanize patterns of reasoning in terms of computation.

LIST SUB-AREAS IN PORTFOLIO:

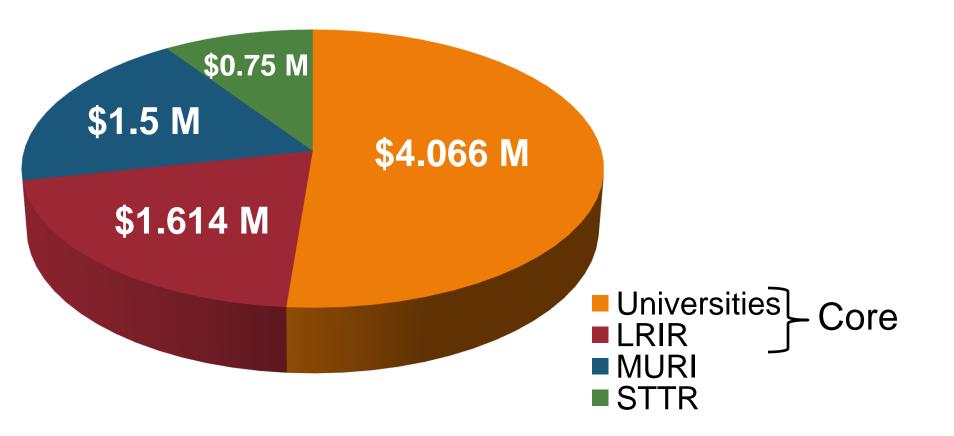
•Sub-Areas	Objectives		
Data Discovery Information Science	 Discover structures in data and shape them into information Methods for fusing heterogeneous data Higher-level information and computation 		
Algorithmic Development Statistical Modeling	 Exploit structures Leverage a priori models To improve processing		
Sensors & Radars Communication Networks	Fusion of sensors and fusion of network data for detectionPerformance of sensor fusion		





Portfolio (FY12)









Air Force Relevance





Program Contribution:

Information Triage

Automated Reasoning

Human-Machine Interface

Formal Verification

Cyber Domain



Intelligence, Surveillance, Reconnaissance

Space Situational Awareness



Collaborations & Transitions



- OSD/ONR Data to Decision
- OSD/AFRL/RH Autonomy
- DARPA/AFRL/RY Mathematics of Sensing, Exploitation and Execution (MSEE)
- ARO's MURIs:
 - Multivariate Heavy-tailed Statistic
 - Revolutionizing High-dimensional Microbial Data Integration
- Topological techniques for data analytics transitioned to Army's Phase-II SBIR.
- Compressed-sensing techniques transitioned to Trusted Access Program Office (TAPO).





Future Direction



Sub-Areas	Objectives	
Data Discovery Information Science	 Discover structures in data and shape them into information Methods for fusing heterogeneous data Higher-level information and computation 	Emphasized
Algorithmic Development Statistical Modeling	Exploit structuresLeverage a priori models	
Sensors & Radars Communication Networks	 Fusion of sensors and fusion of network data for detection Performance of sensor fusion 	De- emphasized

Rationales:

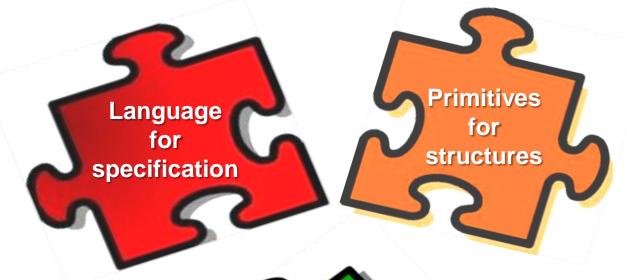
- Avoidance of duplication
- Lack of attention to higher-level information and computation grounded on basic research
- Emerging scientific developments in this research area





Higher-level Information & Computation: Ingredients and Recipes?

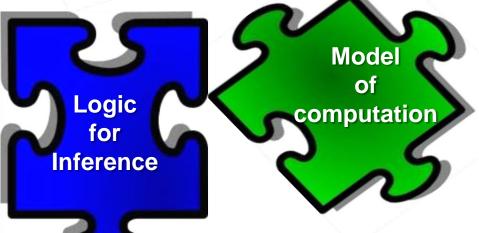




Generic
Programming

Constructive Mathematics

Cognitive Psychology



Program Challenges:

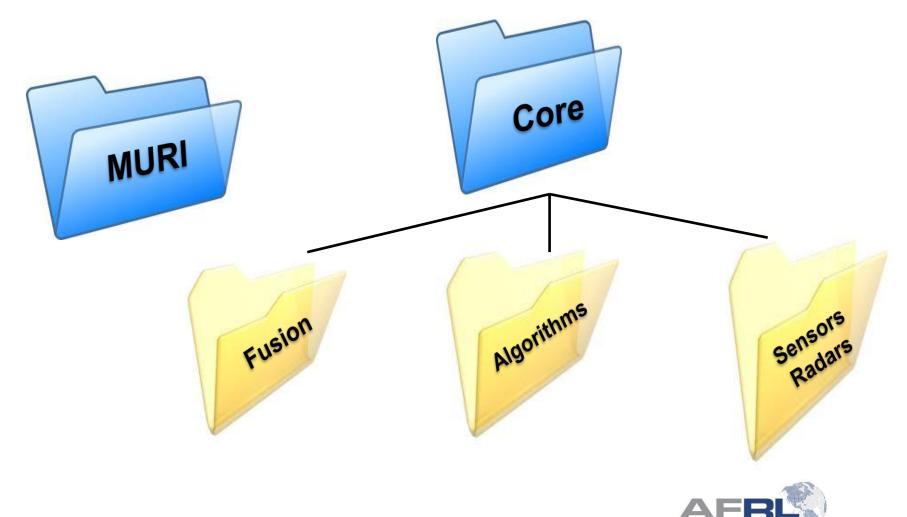
- Higher-order Structures
- Computability





Highlights of Research Projects







Highlights of Research Projects





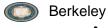








- Jadbabaie
- Koditschek
- Kumar
- Ribeiro



Ramachandran

- Sastry
- Tomlin



Baryshnikov



Minnesota

- Giannakis
- Roumeliotis



Melbourne
• Howard

- Marra
- Moran

Objective: To formulate a new perspective on the *joint control* of *heterogeneous* information sources to simultaneously achieve quantified *informational* and *physical* objective.

Related MURI Topics of ARO:

- Opportunistic Sensing
- Value of Information

AFRL/RY's Involvement:

- Connection with the LRIR project on Layered Sensing
- Interaction between MURI team and RY's technical staff
- Agent for DARPA/DSO's MSEE

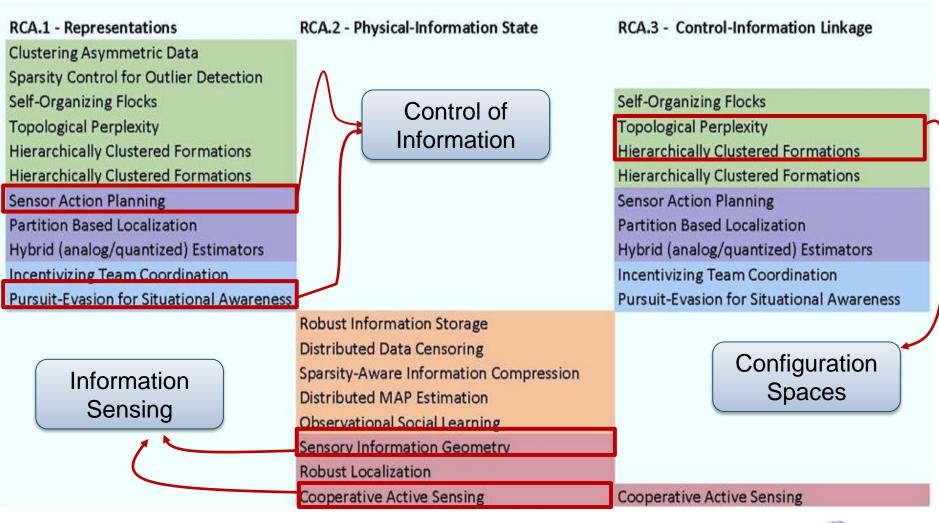
In Connection with AFOSR Programs:

- Intersection with all three sub-areas
- Dynamics and Control
- Sensing, Surveillance, and Navigation





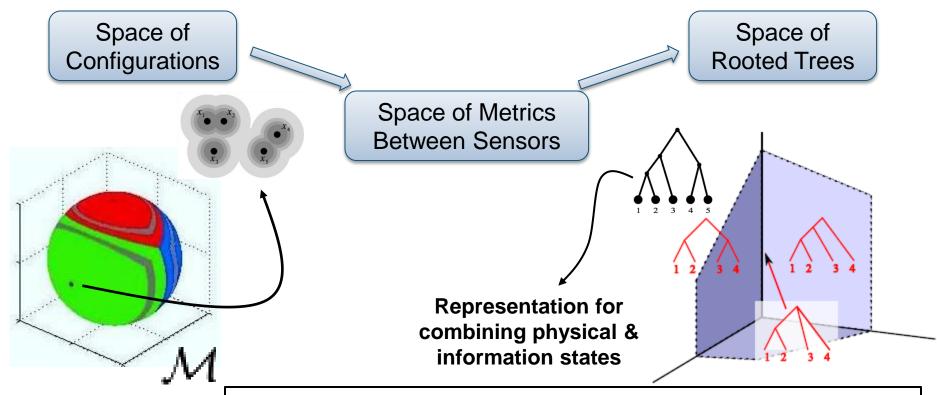














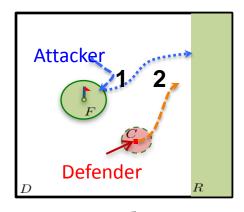
- Investigate the (higher-order) structures of these spaces.
- Formulate control theory on these spaces.
- Formulate information sensing on these spaces.



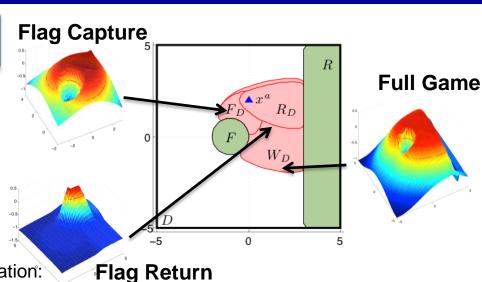








Control of Information



Pursuit-Evasion Game

Initial Condition: $J(x,0) = \phi_R$

Modified Hamilton-Jacobi-Isaacs Equation:

$$\frac{\partial J(x,t)}{\partial t} + \min[0, H^*(x, \frac{\partial J(x,t)}{\partial x})] = 0$$

Subject to: $J(x,t) \ge -\phi_A$

Next: Increasing Game Complexity

- Multiple defenders versus attacker.
- More complex, interactive strategies between the attacker & defender.
- More complicated attacker-defender configurations.









Information Sensing

Model of Sensor

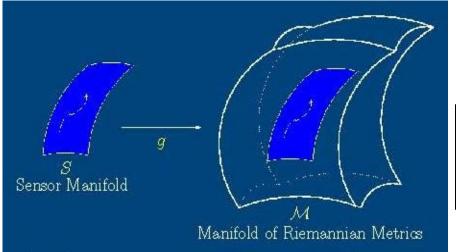
 $f(X;\theta)$

Parameterized by a configuration space S

Sensor Information

$$(\mathcal{I}(\theta))_{i,j} = \mathbb{E}\left[\frac{\partial}{\partial \theta_i} \ln f(X;\theta) \frac{\partial}{\partial \theta_j} \ln f(X;\theta)\right]$$

Idea: each sensor configuration gives a Riemannian metric on ${\mathcal S}$



 \mathcal{M} : infinite Riemannian manifold if S is a manifold

Goal: Study path planning on **S** using structures on **M**

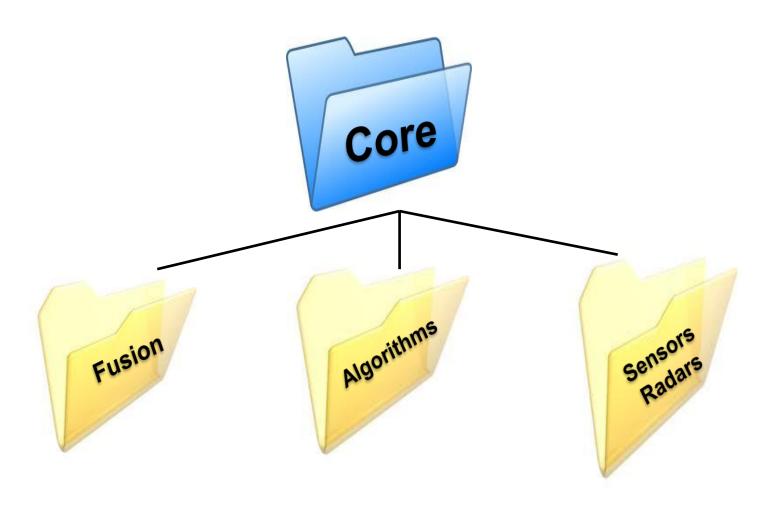






Highlights of Research Projects









Academic Projects in Core Program



•Sub-Areas	Objectives		
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Sensors & Radars Communication Networks	Fusion of sensors and fusion of network data for detectionPerformance of sensor fusion		

Some Pls:

- J. Culbertson (AFRL/RY)
- G. Carlsson (Stanford U.)
- C. Priebe (Johns Hopkins U.) & D. Marchette (NSWC-Dahlgren)
- T. Klausutis, S. Butler, J. Curtis (AFRL/RW)
- D. Blei (Princeton U.)
- R. Devore (Texas A&M U.)
- A. Montanari (Stanford U.)
- A. Hero III, R. Raich (U. Michigan & Oregon State U.)



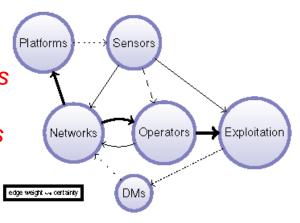


Category Theory & Layered Sensing



J. Culbertson et al., AFRL/RY

- ☐ Project begins in FY12.
- □ Layered Sensing aims to generate *situational awareness* from available resources (*sensors, platforms, networks, human operators, decision makers*) with required *attributes* (*persistent coverage, trusted sensing, information triage, adaptability, understanding social dimensions*)



□ Goals:

- To model *heterogeneous* systems with uncertainty in a *universal* context and *layers* of abstraction.
- To study basic properties of these systems: composability, stochasticity, relations.
- To develop a *model for Layered Sensing* & use this model for *fusion*.

Technical Approach:
Category of Probability
of Spaces

Objects of Study

Probability spaces $(\Omega, \Sigma_{\Omega}, P)$ and maps between them

- \bullet Ω is the event space
- Σ_{Ω} is a σ -algebra on Ω
- ullet $P:\Sigma_\Omega o [0,1]$ is a probability measure





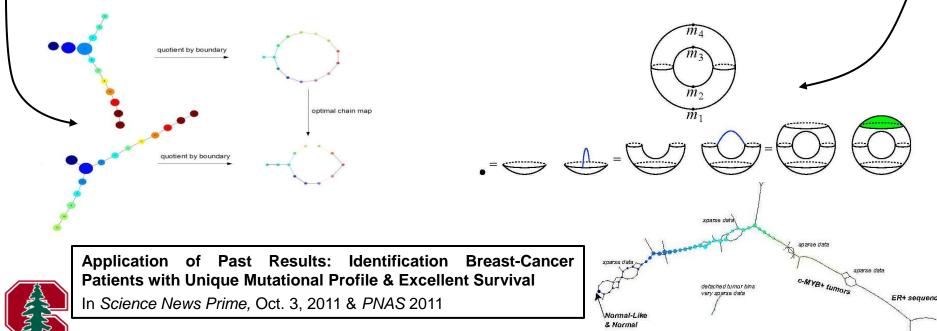
Data Fusion via Topology



G. Carlsson et al.

Current Tasks:

- 1. Data fusion: To study maps between simplicial complexes (models of topological spaces.
- Information discovery: Morse-theoretic decomposition of spaces for finer analysis.
- 3. Sampling issue: To study how different samples affect the outcomes.



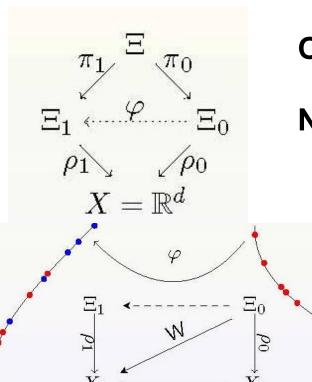
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Data Fusion via Embedding & Matching



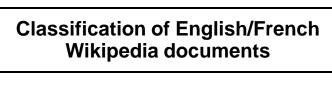
C. Priebe, D. Marchette

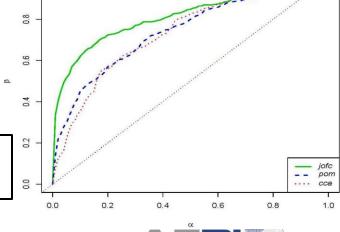


Old: Δ_0 , Δ_1 are used to construct ρ_0 , ρ_1

New:
$$M = \begin{bmatrix} \Delta_0 & W \\ W^T & \Delta_1 \end{bmatrix}$$

Commensurability – W is used for matching **Fidelity** – Δ is used for preserving dissimilarities







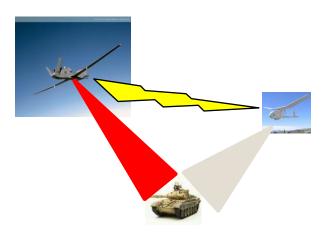
Manifold Embeddings & Target Acquisition



T. Klausutis, S. Butler, J. W. Curtis, AFRL/RW

Mission: Autonomous Target Acquisition

- Find and Fix: Target detection & identification
- Track: Tracking & aimpoint selection
- Assess: Battle damage indication and assessment



Technical Challenges:

- Multiple platforms coordinate to find and track targets
- Computational capabilities vary with platforms
- Platforms may have different sensor capabilities

Scientific Opportunities:

- Nonlinear manifold learning, interactive or supervised learning for classification.
- Low-dimensional data representation and analysis.
- Compressed sensing and information reconstruction.





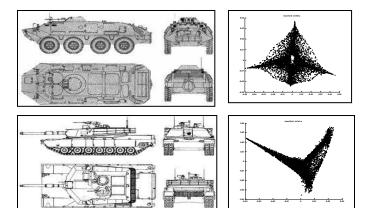
Manifold Embeddings & Target Acquisition



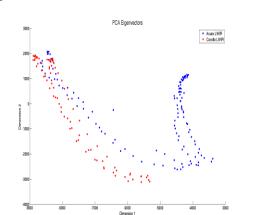
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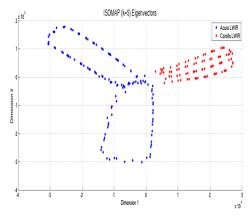
Current Progress:

- Investigating nonlinear dimensionality reduction to reduce computational overhead.
- Comparing PCA and its nonlinear counterparts.
- Verifying the nonlinear techniques on different datasets.



81-D feature vectors reduced to 2-D (Ladar Data)





Separation of Targets: PCA vs. ISOMAP (Synthetic LWIR Data)

Next:

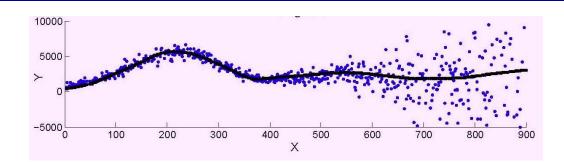
- Study sparse and low-dimensional machine learning in this context.
- Study algorithm's robustness to variations in scale, intensity, etc.



Dirichlet Process Mixtures of Generalized Linear Models



$$egin{aligned} P &\sim DP(lpha \mathbb{G}_0), \ heta &= (heta_{i,x}, heta_{y,i}) | P \sim P, \ X_i | heta_{i,x} &\sim f_x(\cdot | heta_{i,x}), \ Y_i | x_i, heta_{i,y} &\sim GLM(\cdot | X_i, heta_{i,y}) \end{aligned}$$



Key Ideas:

- Local grouping of X and Y with varying mixture components.
- The number of groups need not be known in advance.
- X can simultaneously be categorical and numerical variables.
- A tool that can model many response types and many response shapes.

New Regression Technique

Recent research featured in The Economist



Organising the web
The science of science

The science of science

How to use the web to understand the way ideas evolve

Apr 28th 2011 | from the print edition

COMPUTER scientists have long tried to foist order on the explosion of data that is the internet.

One obvious way is to group information by topic, but tagging it all comprehensively by hand is impossible. David Blei, of Princeton University, has therefore been trying to teach machines to do the job.







High-dimensional Approximation



R. Devore et al.

Scientific Problem: How to recover a function in high dimension with small errors when only a finite number of evaluations are known?

Assumptions: (1) some form of sparsity

(2) reduced number of independent variables.

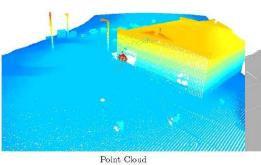
Theorem (DeVore-Petrova-Wojtaszczyk) Suppose that

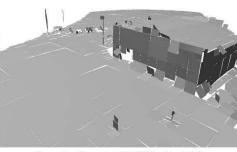
- $f \in C^s(\Omega)$
- There is a g and j_1, \ldots, j_d (both unknown to us) such that $||f(x_1, \ldots, x_D) g(x_{j_1}, \ldots, x_{j_d})||_{C(\Omega)} \le \epsilon$.
- By making $n = C(d, S)L^d \log_2 D$ non-adaptive point queries we can recover f by \hat{f} to the accuracy

$$||f - \hat{f}||_{C(\Omega)} \le C(S, d) \{ ||g||_{C^{s}([0,1]^{d})} L^{-s} + \epsilon \}$$

Another Project: Reconstruction, compression of terrain point cloud data using simple function approximation







AFRL



New Framework for Compressed Sensing



A. Montanari et al.

New joint work with D. Donoho and A. Javanmard

Result - Suppose $x \sim \rho_x$. Sensing matrix A of this type can be constructed such that:

- If y = Ax is observed, then x can be recovered with high probability under some hypotheses on m, n, and ρ_x .
- The recovery is robust to noise.

Notes: There are instances in which this new result supersedes the current one. Sparsity of \mathbf{x} is replaced by $\mathbf{x} \sim \boldsymbol{\rho}_{\mathbf{x}}$ and other hypotheses on \mathbf{x} .





Sensor Fusion via Shannon/Rényi Entropy

A. Hero III, R. Raich

Motivation: Sensor fusion via Shannon's information theory requires computation of entropy or divergence. **Nuisance**: Joint probability density function is not known.

$$G(f) = \int g(f(x))f(x)d\mu(x)$$

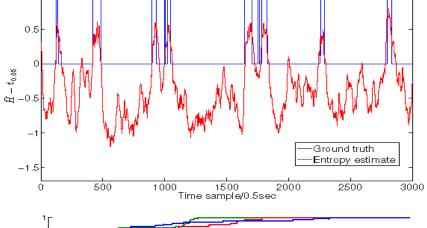
Estimator
$$\hat{\mathbf{G}}(f) = \frac{1}{N} \sum_{i=1}^{N} g(\hat{\mathbf{f}}(\mathbf{X}_i)).$$

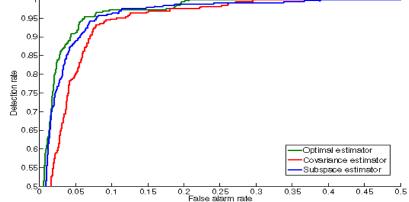
samples

$$\{\mathbf{X}_1,\ldots,\mathbf{X}_N,\mathbf{X}_{N+1},\ldots,\mathbf{X}_{N+M}\}$$

Result:

- Derive Variance & Bias
- Establish Gaussian central limit behavior
- Extend to more general cases







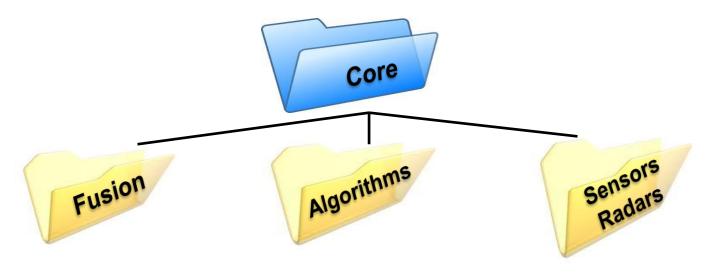




Summary









- To formalize and mechanize information-related concepts in a computational framework.
- Constant need to develop more techniques to deal with diverse types of information.
- Bridging the gap between humans and sensors in the information domain.





Science of Information, Computation and Fusion



Thank You!



